

Applying Machine Learning to MOMA Science Data for Science Autonomy

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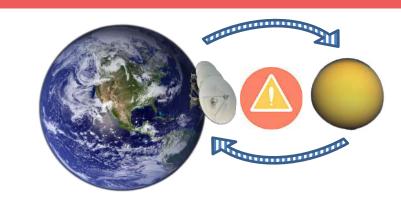
Poster ID: 54

New spectra

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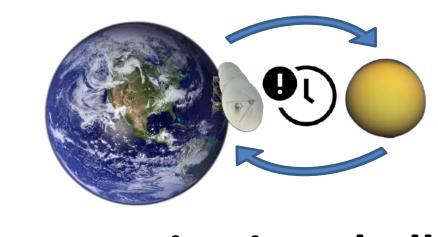
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Space Exploration Context



Ground-in-the-loop limitations

Remote destinations and shorter at-target mission lifetimes limit or preclude ground-in-the-loop interactions



Communication challenges

Remote destinations and extreme environments involve longer communication delays and smaller data downlink capacities

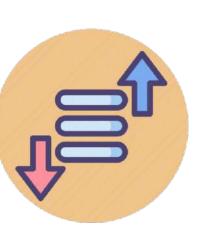
Solar powered 300

kg-class rover



Detection challenges

Scientists will not be able to guide spacecrafts' instrumentation in detection opportunistic features of interest

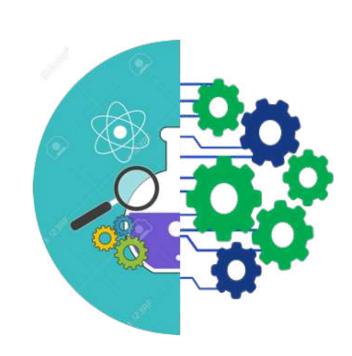


Data prioritization

Future instruments will certainly generate more data: data prioritization is vital to optimize mission science return

Transmit to

Earth



Science Autonomy

The ability of a science instrument to analyze its own data in order:

- to **calibrate** itself
- optimize ops parameters based on real-time findings
- on scientific observations
- prioritize and send back first

ExoMars Rover Mission

Objectives

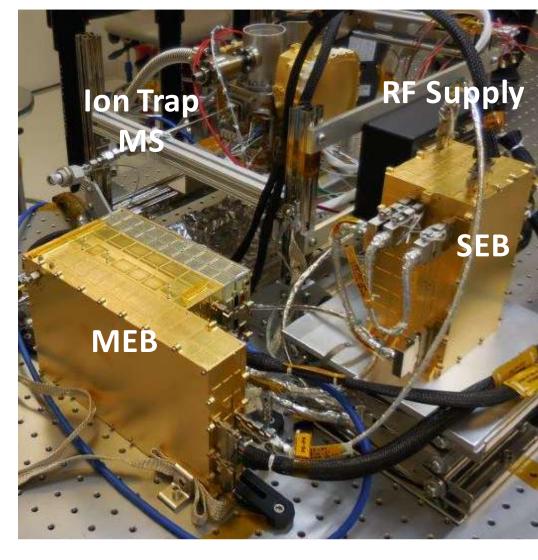
- To search for signs of past and present life on Mars
- To investigate the water/geochemical environment as a function of depth in the shallow subsurface

Instruments

- Drill samples delivers below the surface to the crushing station
- Mars Organic Molecule (MOMA): Analyzer Mass 2 m (4x50 Trap Linear lon Spectrometer
- Raman Laser
 - Spectrometer (RLS): spectral analysis
- MicrOmega: (near IR imaging the samples hyperspectral microscope), mineral identification informs MOMA and RLS of regions of interest to target

MOMA instrument

Dual-source linear ion trap mass spectrometer coupled to pyrolysis/ derivatization-GC (GCMS mode) and UV laser for desorption / ionization (LDMS mode) of crushed rock samples



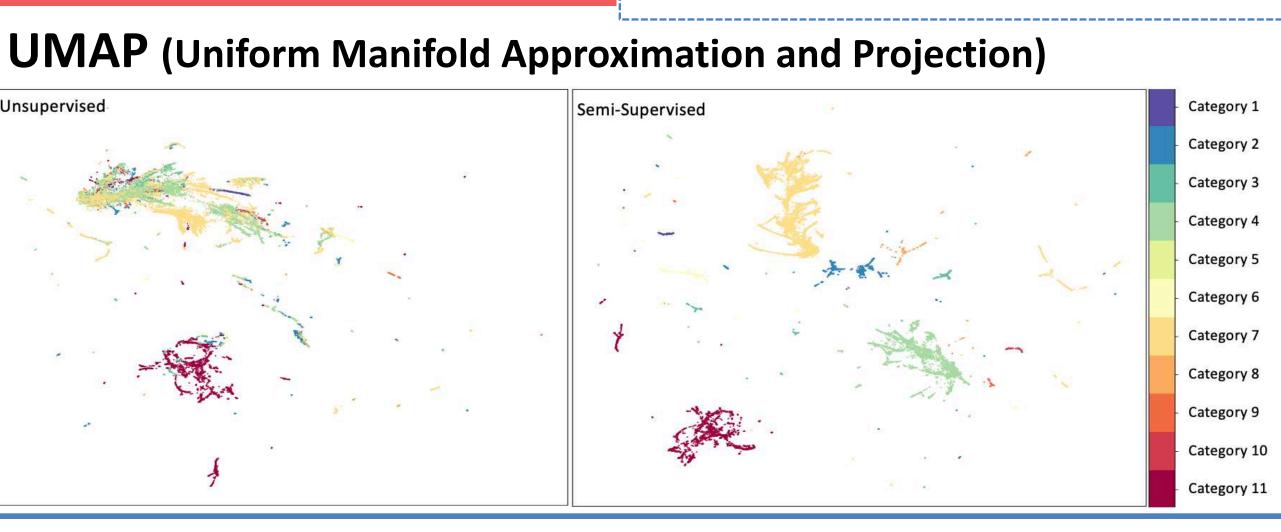
Seeks the *molecular* signs of life with *broad* sensitivity to organics and analysis of chirality

Machine Learning process

Motivation: The MOMA science team may only have a few hours to analyze the delivered data from Mars and to determine what further experiments

should be done to meet the mission's science goals. We are investigating the use of ML to help the science team by matching Flight Model (FM) data from Mars to similar data from tests performed with the Engineering Test Unit (ETU) on Earth.

Initial results



from **ETU**

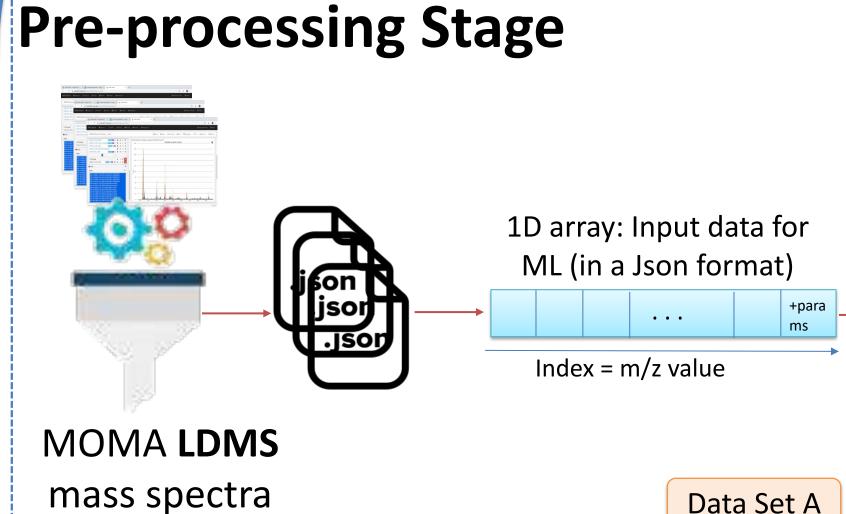
- Assists in high dimension data visualization
- Provides a Semi-Supervised method to help further cluster our data
- Possibility to add new unseen data into an existing embedding space
- UMAP Reduced data can be used as a preprocessing step of Supervised Learning

make mission-level decisions based

determine which data products to

from Mars

Collect spectra



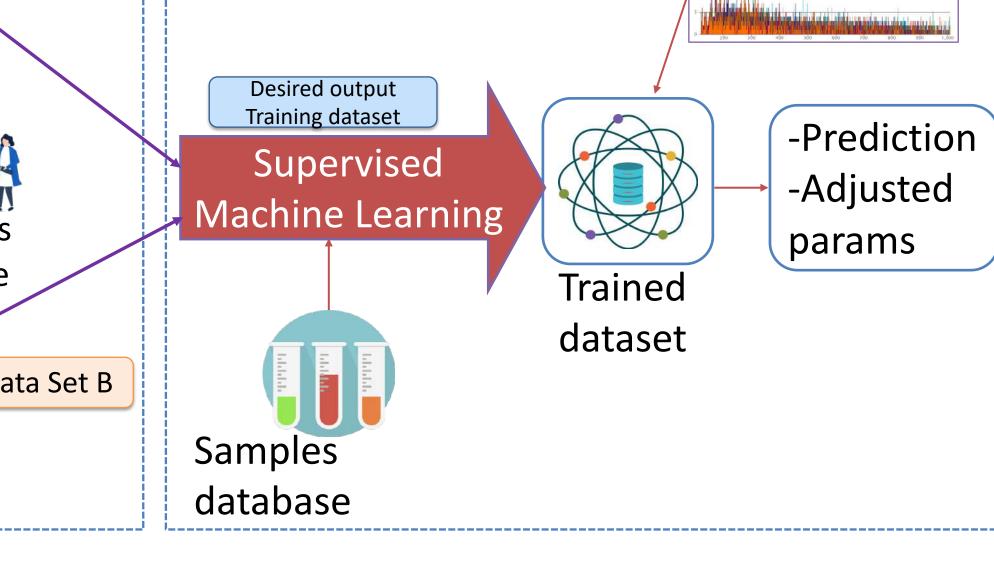
Unknown output No training dataset Data Set A

Filtering Stage **Matching Stage** Desired output Scientists Training dataset Unsupervised Machine Learning expertise Data Set B

Analyze

(ML process)

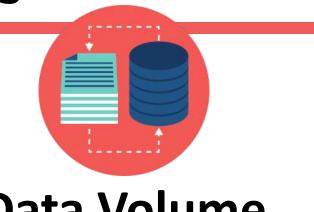
Update Experiment Send to Mars More data



Other results: (feel free to contact me)

- Data Processing: dimensionality reduction, outlier detection,
- Filtering Stage: clustering algorithms
- Matching Stage: neural network development, implementation and CAL interface

Key Lessons



Data Volume

Challenging acquisition of large datasets acquisition for ML trainings



Team Efforts

Crucial collaboration between scientists and data science team



Resource Limits

Desired performance and available resources tradeoffs (CPU, memory)



Trusting ML

Dev. of a "Trust Readiness Level" index (like TRL in engineering dev.)